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Analysis of factors causing volatility in the mask-related stock market during the global pandemic (COVID-19)

Supervisor
Ch. Prof. Carlo R. M. A. Santagiustina

Graduand
Han Bai
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883154

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Contents

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Abstract
Covid-19, the medical community officially recognized and discovered it as a new kind of disease for the first time on December 26th, 2019. Then it quickly spread in many countries around the world in early 2020. Wearing masks has proven to be one of the effective measures to stop the spread of this epidemic. Face masks, which are ordinary in normal life, suddenly became a precious item during the early stage of Emergency Global Pandemic. At the same time, we found that the stock price of masks-related markets in various countries have fluctuated. We will establish relevant models from the aspects of politics, the number of infected people, and the media in various countries to explore the real influencing factors behind them and the connection between various factors and the stock market.

Key words : Covid-19, Face masks, Stock markets, Lockdown stringency, Search engine data

1. Introduction

1.1 Background

In December 2019, an outbreak of a new coronavirus, later called SARS-CoV-2, was discovered in Wuhan and hence communicated to the international community.[1] Subsequently, in early 2020, Covid-19 (coronavirus disease 2019) quickly spread to many other countries around the world . In March 2020, the WHO announced that initially localized epidemics had turned into a "global pandemic."[2] Wearing surgical and FFP masks was one of the most affordable and cost-effective means to stop the spread of Covid-19. The World Health Organization recommended that governments should encourage people to wear masks in public. As the pandemic became more and more severe, consumer demand for personal protective equipment such as masks rapidly increased.

China was the first country to experience a major outbreak of Covid-19. The local government quickly adopted a series of policies on the advice of infectious disease experts to control the spread of the disease. These policies included wearing face masks and quarantining residents at home. All the tourist sites and entertainment places where people gather were closed. The number of new infections and deaths were reported daily. Each community was organized with a dedicated civil servant responsible for notifying each household of news, to ensure that elderly people living alone could also receive daily news instantly, to understand the severity of the situation, and to ask them to wear masks to protect themselves and others. In some remote villages, community servants also used radio and drones to remind people not to go out unless necessary, and to monitor whether they were wearing masks when they went out. Officials who did not seriously carry out policies disease prevention and control policies were dismissed. Under the fear of thousands of new cases every day and inspired by government's determination to fight the epidemic, people have responded to the government's call and began to

purchase and wear masks.

Soon a new problem appeared, because of the limited inventory and the large daily demand for masks, the shortage of masks broke out. Face masks, which were easy to find in ordinary times, suddenly became a precious item. Face masks were rapidly sold out in every pharmacy. Even in hospitals and other places that were on the front line of the epidemic, face masks were in short supply. Consumers, out of concerns for the future, showed unusual consumption behaviors, such as panic buying and hoarding of masks. This created a vicious short-supply circle. At that time the disease had not spread in the rest of the world, and many other countries helped China one after another, sending many personal protective equipment and donating a large number of masks. Some overseas Chinese are also actively purchasing masks from all over the world and sent them to China. On March 18th, Wuhan, China, reported that local new cases returned to 0 for the first time. But the pandemic began to spread all over the world. Eastern countries such as South Korea and Japan have taken similar measures to China, implemented the prevention policies based on wearing masks and quarantining residents at home.

But the situation was not the same in western countries. When the pandemic first spread in Western countries, some countries initially did not understand the severity of the Covid-19 outbreak and regarded it as a common flu, because its initial symptoms were very similar to flu. In the United States and the United Kingdom, the government did not take immediate measures and did not recommend its citizens wear masks. The UK even tried absurdly to adopt a herd immunity approach to combat the pandemic by letting it spread and announced this strategy on March 13. Then the pandemic was completely out of control. The implementation of the herd immunity strategy in the UK ceased in less than two weeks. On May 11, the British government advised the public to wear masks for the first time. In the United States, the coincidence of the pandemic outbreak with the presidential election campaign had made the wearing of masks a politicized and symbol. Masks had become a "new symbol of partisan culture war."[3] American society initially resisted WHO call for wearing masks, even for people without illness. Although wearing a mask is a low-cost protection method that can help reduce the spread of the virus, it took some time before before this policy received a broad endorsement in the US's political and scientific community. In particular, the signals released by the leaders' speeches and deeds inevitably affected the public response. Trump initially refused to wear masks in public, and he also believed that wearing a mask would "look ridiculous" and "harm his reelection chance."[4] He said that restarting the economy rather than responding to the public health crisis was the first priority. Americans hence regarded not wearing a mask as an act of support for the Trump administration. Meanwhile, the number of new daily cases in the United States repeatedly reached new highs. Since March 2020, there have been from 20,000 to 30,000 new cases every day. In fall 2020, it even soared to 200,000 new cases per day, which is ten times as much as before. The US medical system was close to collapse. The highly contagious nature of the virus has changed people's attitudes. On July 01, 2020, Trump changed his initial position and spoke to Fox Business Network that "I am all for masks".[5]

In some European countries, people also refused to wear masks in the beginning. They thought that the compulsory wearing a mask would imply a loss of freedom and was against fundamental liberties. Wave after wave, governments of various countries realized that they should adopt stricter policies, such as staying at home, maintaining social distancing, wearing masks in public places, etc., and strengthening sanctions for offenders to deal with this pervasive virus. At the same time, as people's awareness of

self-protection has increased, people gradually accepted the daily wearing of masks and begun to buy masks in large quantities. People's demand for masks hence progressively increased. For a time, severe shortage of masks occurred around the world, and the price of masks soared. In some places, people could only buy masks in limited quantities with the prescription of doctors.

In some countries, personal protective equipment such as masks is completely dependent on imports, and the battle for important anti-pandemic products has also begun. Many countries were overwhelmed and quickly issued some export bans on masks. For example, Brazil imposed a mask export ban on March 18, 2020. The United State imposed export prohibition for personal protective equipment on April 03, 2020.[6] Finally, around 98 countries have issued temporary export restrictions for personal protection equipment which includes masks. The export restrictions measures map for PPE masks is shown in Figure 1. which is shown below. All these policies that put national interest first constantly challenged the fragile global supply chain of protective equipments.

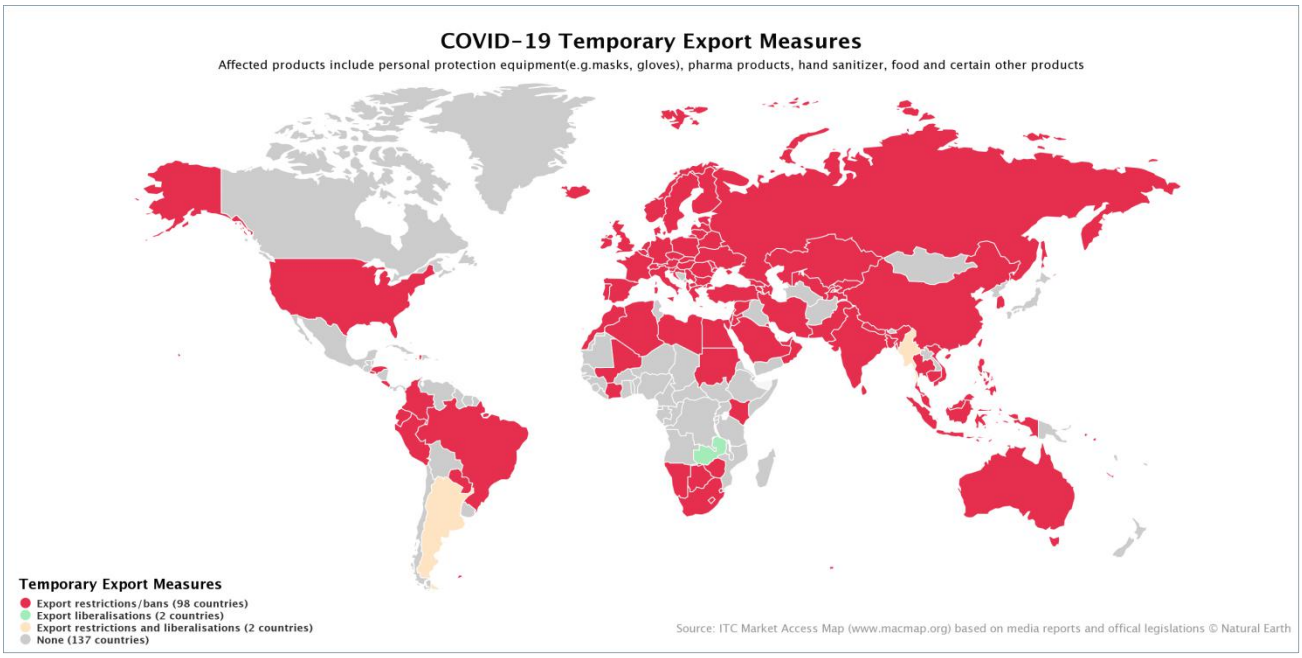

Figure 1. Export measures map of PPE

With the improvement of the situation in some major mask production countries, they work and production gradually resumed. After that stage, the problem of global mask shortage greatly eased. People all over the world gradually started wearing masks in their daily life.

Throughout pandemic outbreak period, the stock price of masks-related markets in various countries were very volatile. This stylized fact triggered this work and determined its research questions: What are the factors causing these stocks' fluctuations during the outbreak? And what are the relationships between country-specific Covid-19 outcomes, like the number of cases, lockdown policies and the returns of masks-related stock markets? The following work is a comparison and analysis of the cultural collision between East and West regarding wearing masks during the Covid-19 pandemic. We start by analyzing the epidemic factors that may explain mask-related stock fluctuations. After presenting the data strategy, we estimate two country-specific VAR models to explore the aforementioned relationships

and answer our research questions.

1.2 Culture collision behind masks

Why are the attitudes towards masks in Eastern and Western countries so different? There are some reasons for why westerners appear to be more averse wearing masks. One may hypothesize that, in western countries, cultural stereotypes may represent those wearing a mask as disease carriers.[7] Therefore, if someone wears a mask on the road, it will frighten other people around. In western work culture, if you are sick, you should stay at home and rest instead of going out. And it is relatively easy to take leave for sickness and people are more accustomed to working from home. In addition, with a relatively lower population density, diseases in western countries are spread with more difficulties. In the past few decades, no large-scale epidemics have occurred in western countries, and people are hence not used to wearing masks.[8]

Why are the Orientals used to wearing masks? The culture of wearing masks in Japan is from 1918-1920. At that time, the Spanish flu caused hundreds of thousands of deaths. Following the second wave of influenza pandemic in 1934, Japanese society gradually formed the concept of "wearing a mask when catching a cold to avoid infecting others and causing other people's distress". Japan’s rapid economic growth in the 1950s was followed by increasing levels of air pollution, coupled with the trouble of spring hay fever, as a result more and more Japanese people regarded wearing masks as a common thing. The U.S also experienced Spanish flu in 1918, but why it didn’t form the attitude towards masks like Japan? This may be because after the Spanish flu, the United States no longer has such a high-fatal infectious disease that requires wearing a mask, and there is no problem of air pollution. For China, a densely populated country. Third plague pandemic in 1855, Zhangjiakou plague in 1949, Asian Flu cased by H2N2 virus in 1957, 1968 flu pandemic, 1977 Russian flu, Shanghai hepatitis A (HAV) in 1988 and other highly contagious diseases in history often cause heavy casualties. In the process of fighting with these diseases, the Chinese people have gradually accumulated some experience, such as the importance of isolation and wearing masks. Besides, the most recent painful memory of SARS experienced in 2003 has not disappeared from the mind. The extremely contagious nature of the Covid-19 and the emergence of super spreaders are very similar to those of SARS in 2003. Covid-19 has awakened people's fearful memories of SARS in 2003. So everyone strictly abides to the measures proposed by the experts. The fast reaction speed and short reaction time across the country also avoids the worsening of situations that may hence become more difficult to control. There are also some cities with severe air pollution in China that make wearing masks seem commonplace.

Different cultures and infectious disease experiences in Eastern and Western countries determine different attitudes towards risks and hence wearing masks. I believe that after this pandemic, if highly infectious diseases similar to Covid-19 will occur again in the future, Westerners' acceptance of wearing masks will be higher. After understanding the difference between East and West cultures behind masks, let’s study more about masks-related stock price.

1.3 Masks-related stock returns

Exogenous events that may have nothing to do with the stock market, like natural disasters, political events, tensions between countries and their coverage in news and social media may have an impact on the stock market. For the relation between disasters and stock market. Assume there is a mining company operating normally, then a mining accident or natural disaster occurs suddenly. The company's stock market is bound to be subject to fluctuations.[9] This may be caused by the disaster that triggered investors' concerns about the company's subsequent development. In addition to natural disasters, news medias are also closely intertwined to the stock market. The reason is that the mood of investors can be easily affected by media news, and market events, like market crashes and bubbles, can themselves affect the news. This relationship exists despite some news may be inaccurate or exaggerate the facts, also, the degree of media influence on stock market may vary from market to market and across time. Studies show that news from government-related media, academia, social media and industry media all have impact on the stock market, but the views from academia media have been found to have a greater impact than news from government and industry medias.[10] This also means that the credibility of the academia-related media is higher. Similarly, the communication and enactment of policies can also have a significant impact on stocks. Some policies make the stock market go up, and some will cause the stock market to fall sharply. The fuse of a trade war between countries may be the signing of a policy. For example, during the trade war between the U.S and China, the energy-related stock markets of both countries experienced diverse fluctuations in terms of change sign and magnitude.[11]

In recent years, threatening epidemics with huge infection rate and fatality rate not only threatened people's lives, but also had a significant impact on the stock market. These events include: SARS in 2003, which caused the stock price of Taiwanese hotel companies falling sharply.[12] SARS is the first deadly epidemic caused by the coronavirus. Then, Ebola break out in 2014. A study found that some companies' stock price was related with the distance of their location to the Ebola outbreak.[13] Them, in 2020, begun the Covid-19 global outbreak. From the above we know the outbreaks of epidemics can cause changes in the stock market. But Covid-19 has had the greatest impact in terms of impact magnitude and duration compared with SARS and Ebola, and pandemic will also have dramatic negative impact on the emerging stock markets[14] and most tourism-related industries.[15] But for personal protective equipment, like face masks, the stock market may move differently. Because compared with the situation where other industries are almost shut down, the shortage of personal protective equipment supplies caused the demand and hence the price of the PPE and face masks market to soar.[16] Which factors are related to the shortage of masks and have a direct impact on the mask-related stock market?

All of the above described events, without exception, triggered investors' concerns about the future. As a global emergency event, Covid-19 is full of uncertainty, and this uncertainty affects investor's decision-making through their emotions.[17] When facing a highly contagious and invisible plague, investors can feel very anxious and panic. Decisions made while experiencing these negative emotions can possibly be the causes of the fluctuations in the mask-related market. The daily increases in the number of infection cases and news about mask shortage can also cause public anxiety and concerns. In order to relieve anxiety, some consumers buy and hoard masks in large quantities to enhance their

sense of security. This behavior can make masks even more scarce and hence the market price of masks will grow. Eventually, if widespread, this behavior could cause volatility in the mask-related stock market. On the other hand, closure policies such as home isolation and school closure have reduced people's consumption and demand for masks. The implementation of these polices can effectively alleviate the shortage of masks. The stock market will be affected to varying degrees according to the different intensity of the lockdown and prevention policies implementation. There exists an index to measure the stringency of lockdown policy implementation in various countries.[18] Among these influencing factors, quarantine policies can themselves affect the infection rate and the number of cases.

Based on the above, for the US and China we will take changes in the number of daily cases, mask shortage coverage in newspapers (i.e., share of daily articles containing the expression "shortage of masks") and lockdown policy stringency indexes as three factors that can help us explain mask-related market returns. In part three we will build a model to analyze and discuss the impact of these three factors on the mask-related market. Here I anticipate and briefly describe the hypothesized relationship among these four variables. As shown in Figure 2, mask shortage are expected to have a positive influence on closure policy, media news about shortages and daily cases. Which means the scarcity of masks will lead to stricter implementation of the closure policy and the number of people infected because they cannot be bought will increase. At the same time, news about the mask shortage will be reported more frequently. Closure policy will have both negative influence on daily cases and mask-shortage situation. It is not difficult to understand that the tightening of the closed policy can reduce daily cases, and it can also alleviate the shortage of masks. Daily cases increasing and media news reported more frequently will lead to mask supply tension increased, thereby making masks more scarce. So both media news and daily cases have positive effect on mask shortage. Finally, The shortage of masks directly leads to price of mask changes, which affects the masks- related stock masks.

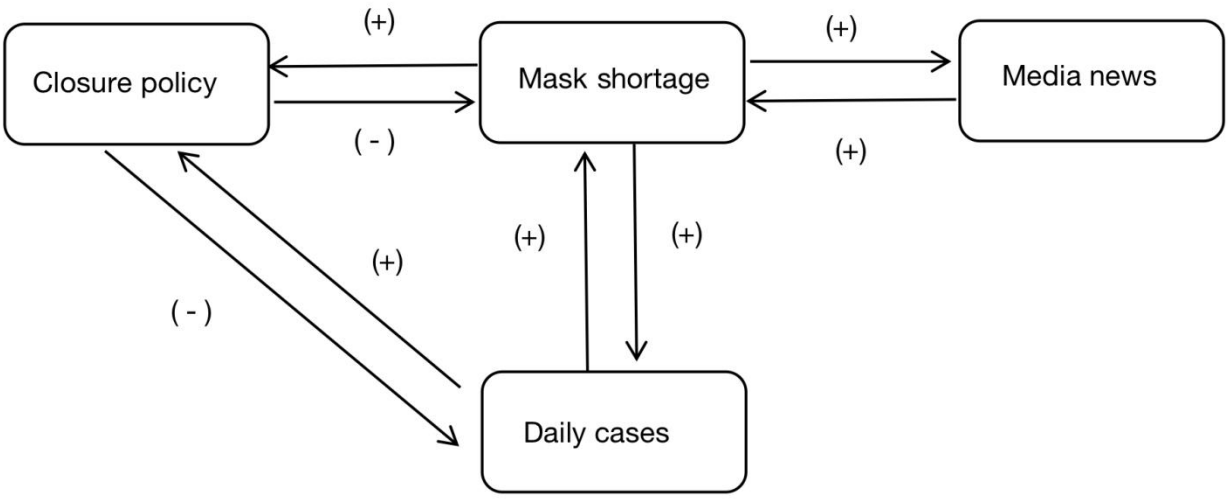

Figure 2. Predicted interaction of three factors

Note: mask shortage is the situation of mask in real market, here it as an intermediate variable for better understanding relationships of other factors.

After having described the influencing factors and their theoretical relations, we need to determine the specific variables that will be used in our model before we can start the analysis. In order to do that, we need understand the mask industry first. The following are some investigations and studies on the mask industry supply chain.

1.4 Mask industry supply chain

According to the report of global masks value chain, which shows in 2017, China's export share of masks accounts for 41% in the global market and that of the United States is 18%. We can see this below in figure 3. The total exports of the two countries exceeded 50% of the world's supply before Covid-19. After the Covid-19 outbreak, under the leadership of the Chinese government, China's exports of masks account for 56% of the world's total supply, which corresponds to an increase of 15% compared to the share before the pandemic. In the field of global supply, China and the United States are the two most critical players. So we selected China and the United States as the research objects.

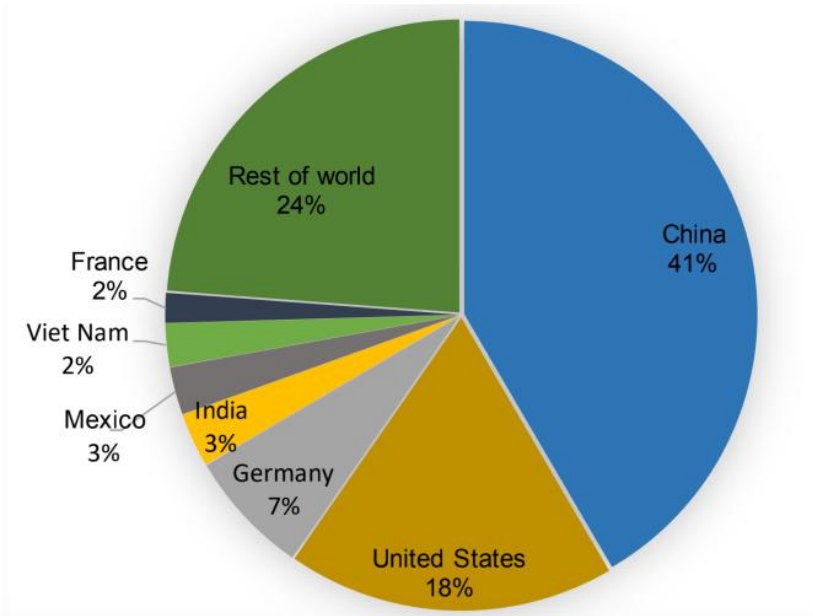

Figure 3. Share of exports of face masks, by country, 2017

The upstream of the medical mask industry chain is polypropylene, rubber and other petrochemical raw materials. The midstream of the mask industry chain is non-woven enterprise, which use raw materials such as polypropylene to produce spunbond and meltblowm non-woven fabrics. Common disposable medical masks are mainly made of three layers of non-woven fabrics: the innermost layer is spunbond; the middle filter layer uses meltblown. the outermost layer is spunbond with waterproof. The downstream of the medical mask industry chain are terminals such as hospitals and pharmacies. Manufacturers distribute the medical masks to hospitals, pharmacies and other terminals, and ultimately use them for in-hospital protection or retail.[19] The whole mask industry chain is shown in Figure 4 below.

As the most important material for making masks, that is polypropylene, is located in the upper reaches of the mask industry chain. Changes in the polypropylene stock market will also affect the mask stock market in the middle and lower reaches of the industrial chain. For this reason we selected the polypropylene stock market as the research object in this work, using its time-series as a proxy for whole mask-related industry.

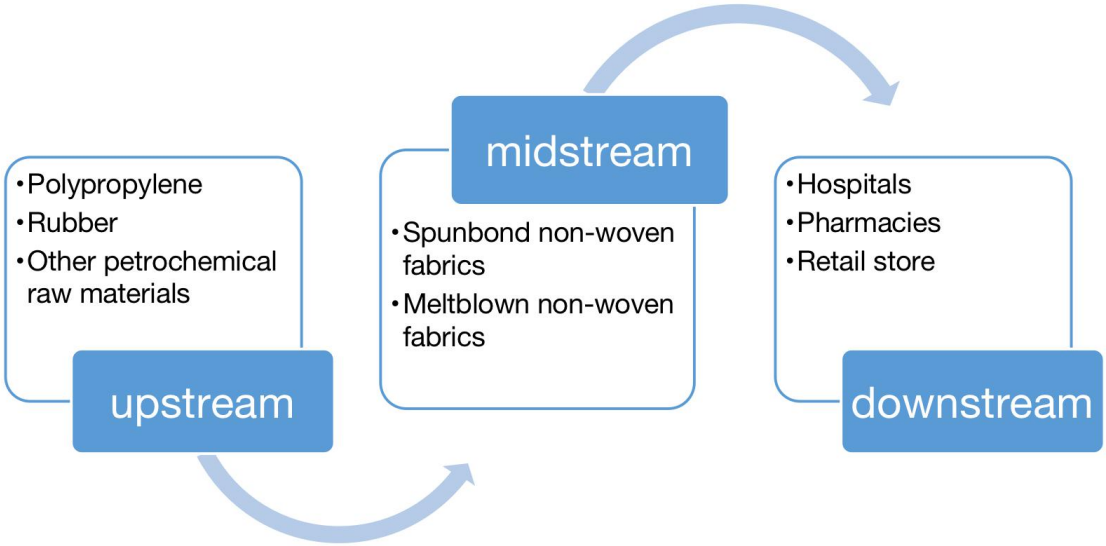

Figure 4. Mask Industry Chain

1.5 Research purposes

The purpose of this research is to establish relevant models based on three influencing factors (government policy, daily new cases and media news) and polypropylene stock market, and use this model to explore the relationship between them. We set China and the United States as research background countries, all the data are from China and the U.S Finally we will also compare the results between two countries.

2. Data Collection

2.1 Stock returns

Stock market data at a daily frequency has been download from Yahoo finance. We collected the daily stock price for 339 trading days in Chinese stock market and 353 trading days in United States stock market period from January 1, 2020 to May 28, 2021. And then calculate simple returns based on the adjusted close price. This is the formula used for calculating simple returns:

$$R_t = (S_t - S_{t-1}) / S_{t-1}$$

Where: R is daily return, S is stock price

China

Shandong Dawn is one of the enterprises producing polypropylene in China. In 2019, the company's polypropylene accounted for about 20% of the parent company's sales revenue. Dawn responded to the call of the Chinese government during the outbreak of the Covid-19, adding 700 tons/day of polypropylene production capacity to the existing production line, with a maximum total production capacity of 1,200 tons/day. The specific stock price changes are shown in Figure 5 below. It can be clearly seen that there is a peak in the figure on March 9, 2020. After that, the stock price gradually decreased. This key time point and the trend of stock price change is similar to Tianjin TEDA, which is also a companies that produce polypropylene shown in Figure 6. And we choose Shandong Dawn as the representative company of China to study in this paper.

Figure 5. Stock price of Shandong Dawn

Figure 6. Stock price of Tianjin TEDA

United States

ALPEK operates one of the largest polypropylene plants in America and it owns the largest polypropylene facilities in North America. The company's stock price began to decline in January 2020 and reached its lowest point on March 30. This trend is similar to Braskem, which company own 5 polypropylene plants in America. We choose ALPEK as the representative company of United States to study in this paper.

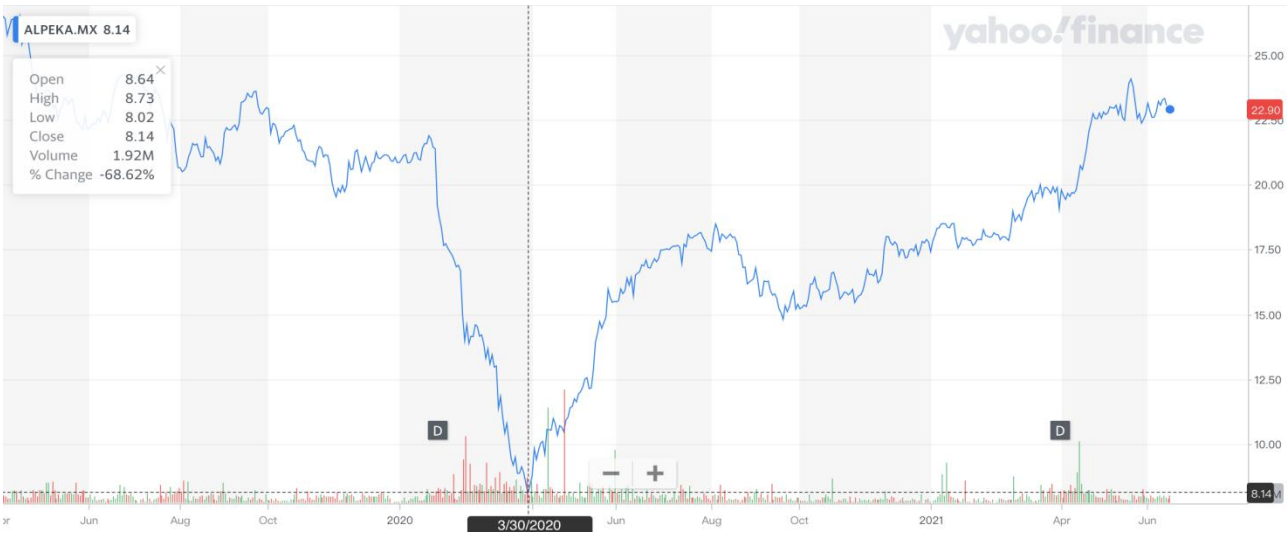

Figure 7. Stock price of ALPEK

Figure 8. Stock price of Braskem

2.2 Trend of daily new cases

The data of daily new cases and confirmed cases of China and United States are all downloaded from the WHO official website. We obtain the daily new cases for both China and United States from January 22, 2020 to May 29, 2021. We put the pictures of new cases and confirmed cases together below. At the peak of the pandemic, sometimes the number of daily new cases will up to tens of thousands, even hundreds of thousands. This brings difficulty to our subsequent calculation and plotting. So I organize these data and calculate the ratio of the daily new cases to the maximum new cases in a single day. Finally these data will be presented in the form of proportions from 0-1.

China is the first country where the pandemic broke out. There is only one wave from January 2020 to March 2020. After that, There are only a few new cases every day, indicating that the pandemic has been well controlled. As shown in figure 9.

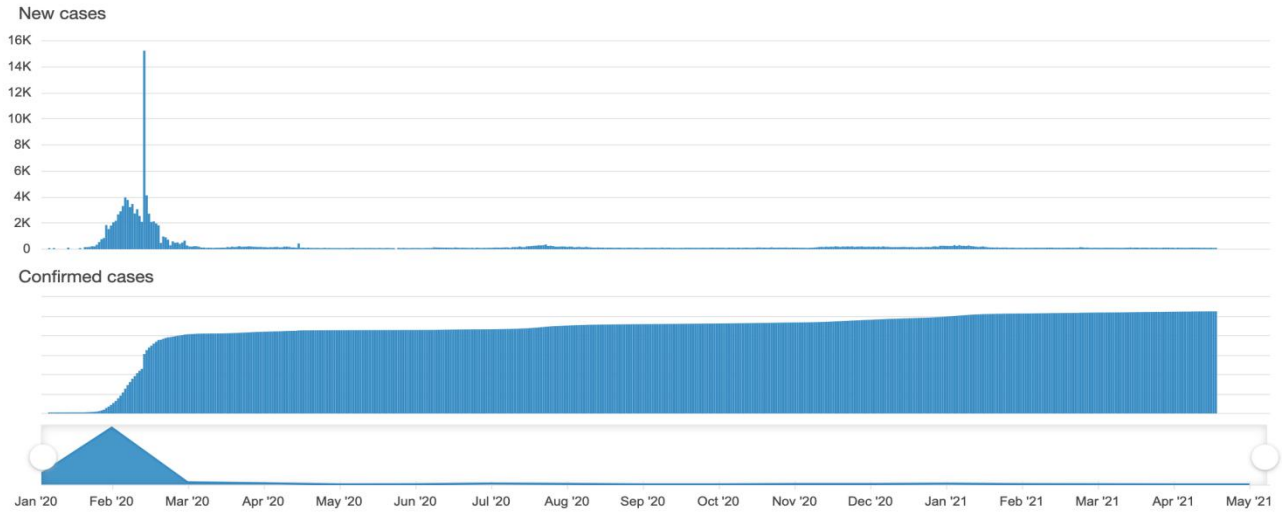

Figure 9. Daily cases of China

While in United States, situation is completely different from China. Figure 10 shows it has experienced more than one wave of the pandemic. The first wave was in April, 2020. After two waves, it ushered in the worst wave from October 2020 to February 2021.

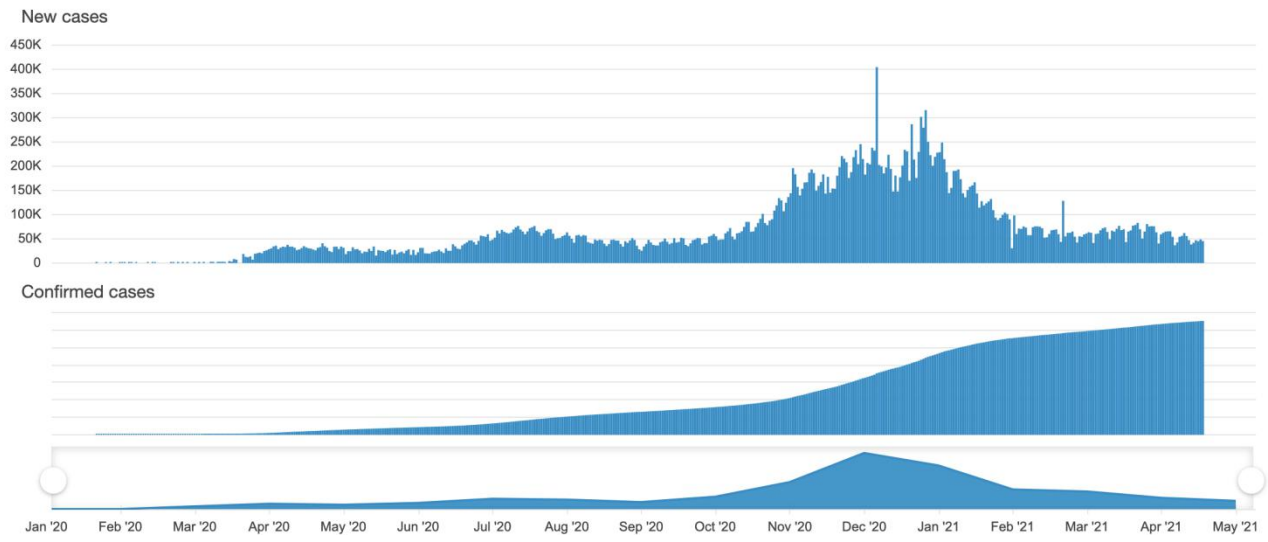

Figure 10. Daily cases of the U.S

(Data reported to WHO in the last 24 hours. Latest update: 9 May 2021, 04:43 pm CEST)

2.3 Lockdown stringency index

The data is download from Oxford COVID-19 Government Response Tracker (OxCGRT), which is a global panel database of pandemic policies. It collects information on the policies issued by various countries around the world in response to the pandemic. We obtain the data of both China and United States from January 1, 2020 to May 17, 2021. There are 23 indicators in this database. Each indicator of the local government gets a score between 0-100 according to the strictness of the law. We can choose the indicator that you want to follow and track how this indicator change in a period. This indicator is based on five components:

- C - containment and closure policies (contain indicator C1-C8)
- E - economic policies (contain indicator E1-E4)
- H - health system policies (contain indicator H1-H7)
- V - vaccination policies (contain indicator V1-V7)
- M - miscellaneous policies (contain indicator M1)

As one of the factors that we will study is closure policy, we use country-specific stringency indexes to proxy it. These indexes can be considered standardized measures of the strictness of each country's closure policy. I download timeseries of stringency index which include all C indicators (All containment and closure policies) and H1(Public information campaign policy) from OxCGRT. Details of policy name could be found in below Table 1. OxCGRT indicator coding.

Table 1. OxCGRT indicator coding

ID	Name	Type
Containment and closure		
C1	School closing	Ordinal
C2	Workplace closing	Ordinal
C3	Cancel public events	Ordinal
C4	Restrictions on gathering size	Ordinal
C5	Close public transport	Ordinal
C6	Stay at home requirements	Ordinal
C7	Restrictions on internal movement	Ordinal
C8	Restrictions on international travel	Ordinal
Economic response		
E1	Income support	Ordinal
E2	Debt/contract relief for households	Ordinal
E3	Fiscal measures	Numeric
E4	Giving international support	Numeric
Health systems		
H1	Public information campaign	Ordinal
H2	Testing policy	Ordinal
H3	Contact tracing	Ordinal
H4	Emergency investment in healthcare	Numeric
H5	Investment in Covid-19 vaccines	Numeric
H6	Facial coverings	Numeric
Miscellaneous		
M1	Other responses	Text

Stringency indexes of China and the United States are shown in Figure 11. From Figure 11 we can observe that China implemented a blockade policy as early as early January 2020, then reached the strictest level of lockdown policy at the beginning of February 2020. Although the number of daily new cases in China has been reduced to just a few since March, the overall lockdown level has maintained the strictest level. The United States began to implement a low-level closure policy in February, mainly to restrict entry of flights from China. Later, due to the arrival of the first wave of the pandemic, the United States gradually adjusted the lockdown policy to the highest level. Until April 2021, the most terrible period of the pandemic in the United States has been passed. As the situation improves day by day, the stringency of the closure policy has gradually declined.

Data processing about this part is not complex. In order to better reflect the impact of daily policy changes on other factors, I made the difference of stringency index between the current day and the previous day. The difference for each day is formed as a set of original data which will be used in our model later.

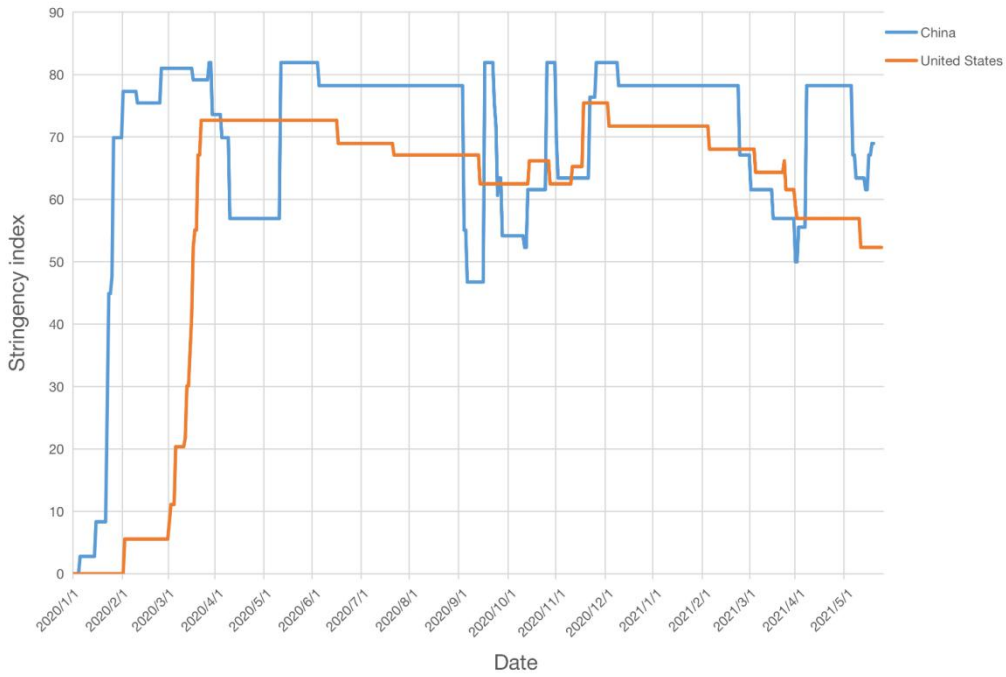

Figure 11. stringency index

2.4 Media news

I searched the keyword “mask shortage” in the Media Cloud web archive, which is an online platform used to capture, filter and count news articles related to specific topics. Here I download the daily percentage of stories (i.e., articles) from United States National media and China National media that mention a “mask shortage”, from January 1, 2020 to May 23, 2021. As expected, the choice of the language of the media source affects the final outcome, and the time series for Chinese and English media show different results. Figure12 shows the shortage stories peak for the United States National media in April 2020. While for Chinese media mask shortage stories share peaks in February 2020, as Figure 14 shows.

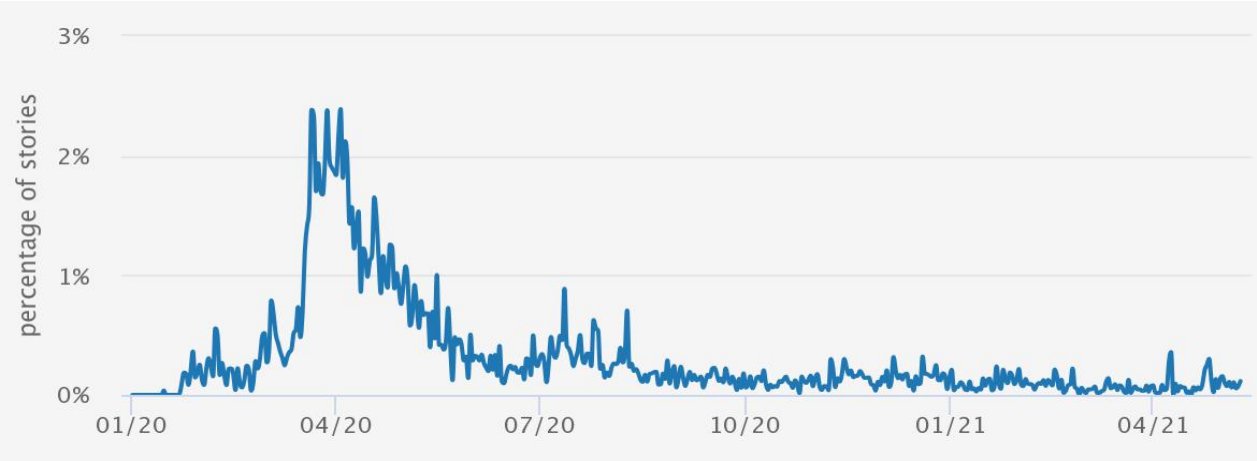

Figure 12. United States - National Media about mask shortage

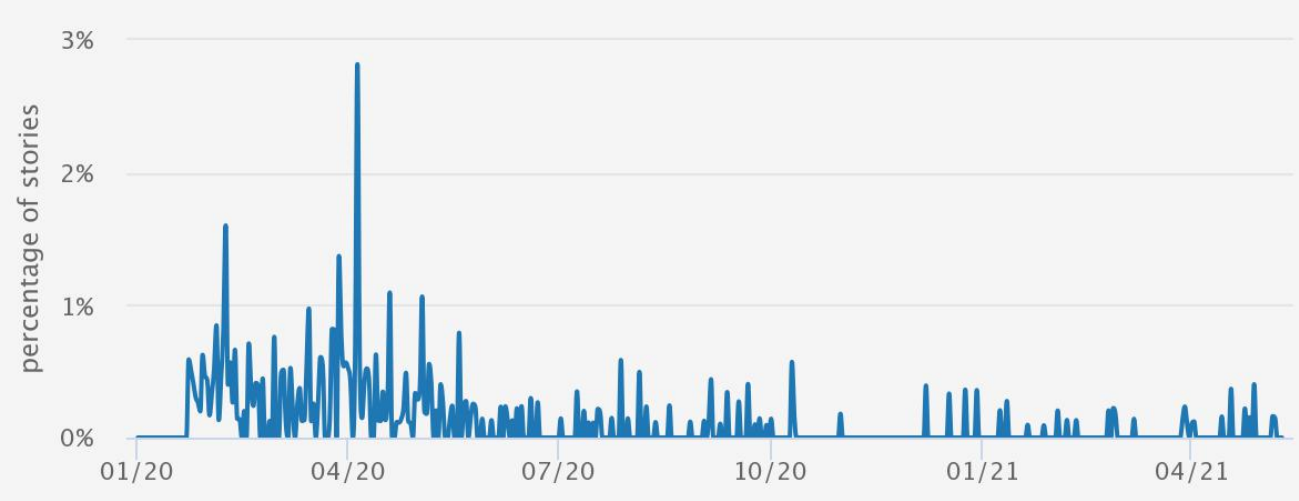

Figure 13. China-National Media about mask shortage—Search in English

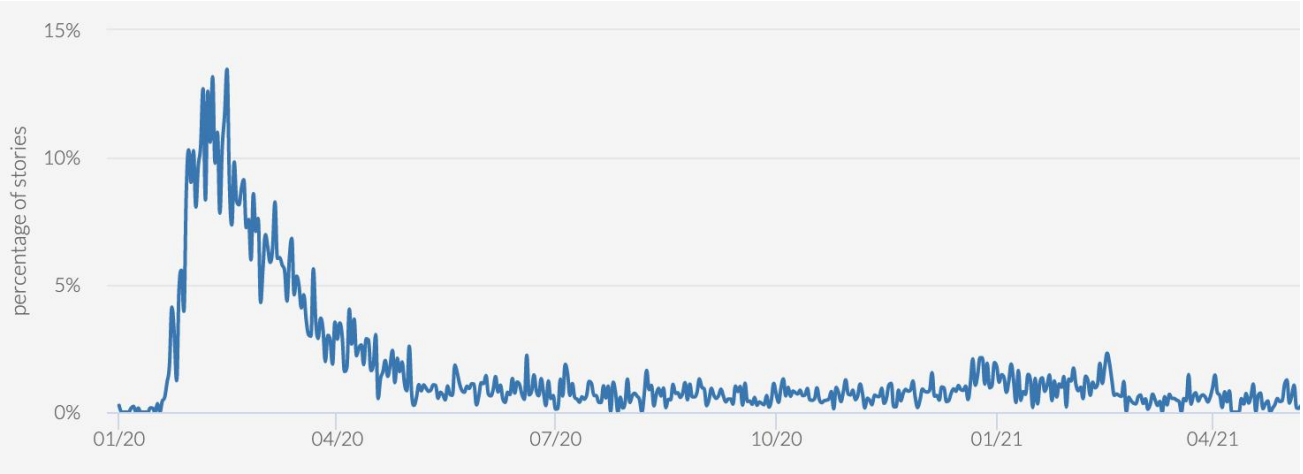

Figure 14. China-National Media about mask shortage—Search in Chinese

2.5 Data cleaning

Because the stock market is not open every day. After collecting and merging all the data, we remove the dates for which we have missing observations for at least one variable (NA value), keeping only the dates intersection for our four time-series. For China the date intersection ranges from January 22, 2020 to May 17, 2021, including 316 days. For the United States it ranges from January 22, 2020 to May 21, 2021, including 334 days.

3. Model

Many works have studied the changes in the stock market during the Covid-19 pandemic, here follows a selection works closely related to this paper. David Carter used the multivariate regression model (MVRM) to analyze and compare the stock markets of travel-related companies during the pandemic.[14] Ajit Mahata developed a model to study stock price during the pandemic which would be helpful to reduce investment risk.[20] Salisu A A use panel Vector Autoregressive (pVAR) model to study oil stock price.[21] In this paper, we choose Vector Autoregression model(VAR) to analyze the relationship among stringency index, daily new cases, mask shortage news and polypropylene stock returns in China and United States.

3.1 VAR model

Vector autoregressive model also be called VAR model, was first proposed by Sim in 1980[22] and was later widely used to predict interconnected time series systems and analyze the dynamic effects of random disturbance items on variable systems. The principle of this model is to construct a model by taking each endogenous variable as a function of the lag value of all endogenous variables in the system.[23] So we usually use it to determine the interdependence and dynamic relationship between variables.[24]

The VAR(p) process is as follows:

$$y_t = A_0 + \sum_{i=1}^{p} A_i\, y_{t-i} + \sum_{j=1}^{q} B_j\, x_{j,t} + u_t$$

Where:

y_t is a set of K endogenous variables

A_0 is a constant terms with K-dimension

A_i are $(K \times K)$ coefficient matrices for $i = 1, \ldots, p$

B_j is a K-dimensional vector containing the coefficients of the j'th exogenous dummy variable;

$x_{j,t}$ is a one-dimensional vector containing the value of the j'th exogenous dummy variable at time t;

u_t is a K-dimensional white noise, with $E(u_t)=0$ and $E(u_t u_t T)=\Sigma u$

In order to apply the VAR model well, we must first determine the the lag order p. We use Akaike Information Criterion (AIC)[25], Schwarz Criterion (SC)[26], Hannan Quinn (HQ)[27] and Final Prediction Error(FPE)[28] to determine lag order for models of two countries.

Table 2. Lag order selection

	AIC	HQ	SC	FPE
China	12	12	1	12
The U.S	4	4	2	4

As what shown in Table 2, the SC is the minimum value of lag, so we chose lag 1 in VAR model of China. But for the U.S, the value of SC is 2. For a more concise and convenient comparison of the two countries, in this paper we use VAR(1) model in both countries with constant terms and set stringency index,daily new cases, mask shortage news and polypropylene stock returns as 4 endogenous standardized variables, then the model became :

$$y_t = A_0 + A_1 y_{t-1} + u_t$$

3.2 VAR(1) Estimates

VAR(1) model of China

The roots of the characteristic polynomial for Chinese VAR(1) model are: 0.9241, 0.2394, 0.13, 0.13. They are all lie inside the units circle which means the VAR equation system is stationary. Then we can do Granger and Instantaneous causality test. The results are shown in table 3.

Table 3. The Granger and Instantaneous causality for VAR (1) model of China

H0	F-Test/Chi-squared	p-value (<0.05)	conclusion
Returns do not Granger-cause Daily new cases, Stringency index, Shortage news	2.04	0.11	Accept
No instantaneous causality between: Returns and Daily new cases, Stringency index, Shortage news	3.70	0.30	Accept
Daily new cases do not Granger-cause Returns, Stringency index, Shortage news	3.68	0.01	Refuse
No instantaneous causality between: Daily new cases and Returns, Stringency index, Shortage news	57.13	2.42e-12	Refuse
Stringency index do not Granger-cause Returns, Daily new cases, Shortage news	3.63	0.01	Refuse
No instantaneous causality between: Stringency index and Returns, Daily new cases, Shortage news	24.98	1.56e-05	Refuse
Shortage news do not Granger-cause Returns, Daily new cases, Stringency index	20.09	1.03e-12	Refuse
No instantaneous causality between: Shortage news and Returns, Daily new cases, Stringency index	48.68	1.53e-10	Refuse

As shown in Table 3, only Returns is neither the Granger cause nor the instantaneously cause of other three factors. Daily new cases, Stringency index and Shortag news are both the Grange cause and the instantaneously cause of other three factors.

Next, we present our model estimate in Table 4, there are total of 16 estimated coefficients of endogenous variables. Among them, 3 coefficients are statistically highly significant at the 0.001 level, 3 coefficients are statistically significant at the 0.01 level and 5 coefficients are statistically significant at the 0.05 level. Which means the impact of independence variable (shortage news on dependent variables (Daily new cases, Returns and Shortage news) is the most significant.

Table 4. VAR(1) estimates for data of China

	Dependent variables:			
	Daily new cases	Stringency index	Returns	Shortage news
L1 Daily new cases	0.13*	-3.17	-0.04	0.02**
L1 Stringency index	3.32e-03**	0.12*	0.001 .	2.21e-04 .
L1 Returns	-0.18 .	-7.30	0.17**	0.01
L1 Shortage news	1.47***	12.93	0.56***	0.89***
Constant	-0.01*	-0.08	-0.01*	1.23e-03*
Multiple R^2	0.26	0.02	0.14	0.88
Adjusted R^2	0.25	0.01	0.13	0.88
Residual SE	0.07	4.36	0.04	0.01
F-statistic	26.77***	1.6	12.46***	555.3***

Note: L1 means once lagged variable.

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

For 4 dependent variables, Adjusted R^2 of Shortage news is the highest of the four (0.88). Adjusted R^2 for Daily new cases and Returns are non negligible (0.25 for Daily new cases and 0.13 for Returns). Which means that through this VAR model, except for the Stringency index, the variations of other dependent variables can be in large part explained using the lagged values of these variables. F statistic for Daily new cases, Returns and Shortage news are all significant.

From above regressions we can claim that the stock returns of polypropylene in China are mainly explained by the lagged values of returns and by mask shortage news. The more news stories about mask shortage, the higher are the returns of polypropylene stock market. The reason may be that the masks shortage news caused people to worried about the raw materials of masks, which stimulated the stock price of polypropylene. Here we can't observe significant effect of Daily new cases and Stringency index on Returns. The effect of other independent variables on the Stringency index is negligeable and non significant. This can be partially explained by the fact that the Chinese government maintained its vigilance against the Covid-19, keeping high level of closure policy, despite decreasing numbers of new cases. Shortage news are effected by lagged Daily new cases as the worse the pandemic situation was, the stronger war the incentive for consumers to hoard masks, and ultimately make the shortage of

masks more severe, and consequently the related media news were increased.

VAR(1) model of the US

The roots of the characteristic polynomial are: 0.9565, 0.468, 0.09494, 0.0001857. They are all lie inside the units circle which means the VAR equation system is stationary. Then we can do Granger and Instantaneous causality test. The results are shown in table 5.

Table 5. The Granger and Instantaneous causality for VAR (1) model of US

H0	F-Test/Chi-squared	p-value (<0.05)	conclusion
Returns do not Granger-cause Daily new cases, Stringency index, Shortage news	0.12	0.95	Accept
No instantaneous causality between: Returns and Daily new cases, Stringency index, Shortage news	13.13	4.37e-03	Refuse
Daily new cases do not Granger-cause Returns, Stringency index, Shortage news	2.18	0.09	Accept
No instantaneous causality between: Daily new cases and Returns, Stringency index, Shortage news	2.88	0.41	Accept
Stringency index do not Granger-cause Returns, Daily new cases, Shortage news	8.10	2.39e-05	Refuse
No instantaneous causality between: Stringency index and Returns, Daily new cases, Shortage news	15.28	1.59e-03	Refuse
Shortage news do not Granger-cause Returns, Daily new cases, Stringency index	5.06	1.74e-03	Refuse
No instantaneous causality between: Shortage news and Returns, Daily new cases, Stringency index	3.79	0.29	Accept

As what shown in table 5, Daily new cases is not the Granger cause and the instantaneously cause of other three factors, but Stringency index is both the Granger cause and the instantaneously cause of other three factors. Returns is not the Granger cause but the instantaneous cause of other three factors. Shortage news is completely opposite of Returns, Shortage news is not the instantaneous but the Granger cause of other three factors.

In Table 6, there are total of 16 estimated coefficients of endogenous variables. Among them, 3 coefficients are statistically highly significant at the 0.001 level and just one coefficient is statistically significant at the 0.05 level. While 12 coefficients are not significant. Two highly significant coefficients belong to the Shortage news equation (see Table 3, column 4), the impact of the lagged values of the Stringency index and that of Shortage news are the most significant. Whereas for Daily new cases the most significant explanatory variable is the lagged value of the latter.

Table 6. VAR(1) estimates for data of the US

	Dependent variables:			
	Daily new cases	Stringency index	Returns	Shortage news
L1 Daily new cases	0.47***	-0.87	0.02	-8.43e-04
L1 Stringency index	-3e-03	-0.02	-1.43e-03	1.53e-04***
L1 Returns	0.05	-2.25	-0.06	3.08e-04
L1 Shortage news	-4.10*	54.40	0.63	0.94***
Constant	0.08***	0.10	-3e-03	2.59e-04*
Multiple R^2	0.27	0.02	0.02	0.92
Adjusted R^2	0.26	0.01	0.01	0.92
Residual SE	0.12	1.96	0.03	0.001
F-statistic	29.69***	1.68	1.53	985***

Note: L1 means once lagged variable.

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

For 4 dependent variables, Adjusted R^2 of Shortage news is very high (0.92) and adjusted R^2 for Daily new cases is also non negligible (0.26). Which means also for the US, except Stringency index and Returns, fluctuations of other dependent variables can be partially explained by lagged values of our four explanatory factors. F statistic for Daily new cases and Shortage news are all significant.

3.3 Impulse response function

The impulse response function describes response of an endogenous variable to a shock (also called innovation) to itself or to another variable. Specifically, it describes the current and future impact on endogenous variables after a unitary shock is applied to the random error term[29-31]. Before we compute and plot impulse response function, let us first observe the residuals variance covariance matrix of the two countries.

Table 7. Residuals Variance Covariance Matrix of China

	Daily_cases	Stringency_index	Stock_returns	Shortage news
Daily_cases	5.154e-03	9.032e-02	1.489e-04	2.395e-04
Stringency_index	9.032e-02	19.043	6.764e-03	5.926e-03
Stock_returns	1.489e-04	6.764e-03	1.640e-03	3.476e-05
Shortage news	2.395e-04	5.926e-03	3.476e-05	6.409e-05

Table 8. Residuals Variance Covariance Matrix of The US

	Daily_cases	Stringency_index	Stock_returns	Shortage news
Daily_cases	1.511e-02	1.061e-02	2.288e-04	-3.569e-07
Stringency_index	1.061e-02	3.857	-9.342e-03	2.369e-04
Stock_returns	2.288e-04	-9.342e-03	6.547e-04	-8.041e-07
Shortage news	-3.569e-07	2.369e-04	-8.041e-07	1.271e-06

From Table 7 we can see that all the covariance among endogenous variables' residuals appears to be positive. Which means these variables are subject intraday shocks with the same sign during the process. The variance of Stringency index is super big compare with other covariance, it is 19.043. It means stringency index owns large degree of discrete. But for Table 8, there are many negative covariance. Which means when one variable is subject to a positive shock the other is subject to a negative one that same day, and vice versa. The variance of Stringency index is also large in this table, it is 3.857. We could expect that an shock from Shortage news will trigger different responses of other variables in China and the United States. Then we can compare the response of the same variable to the impulse(Shortage news) in different country. We use impulse response function to to achieve this.

For our VAR model, we could set orthogonalised[22] and cumulated impulse responses with bootstrapped error bands to compute, the confidence level here used is 68%[32], the number of runs for the bootstrapped C.I. is 200. We set Cumulative response window size to Chinese data for 40 working days, and to the U.S data for 80 working days. In following figures, the black curve represents impulse response function and the red curve represents confidence interval.

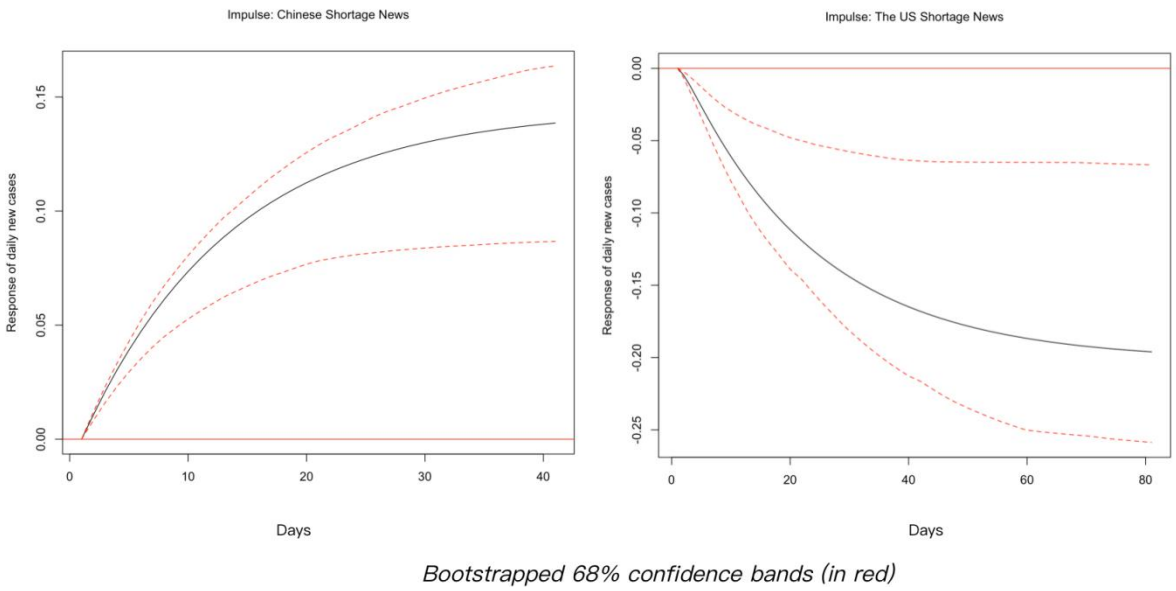

Figure 15. Cumulative responses of Daily new cases to Shortage news between China and The US

From Figure 15. we find that an unit impulse to Chinese Shortage news causes a positive and significant response of Daily new cases. After 30 working days, the cumulative response of Daily new cases reaches its maximum, that is 14%. Steady state of cumulative response means that marginal response after that day is equal to 0. The lower band reaches 8% and the upper band reaches 17%. The US Shortage news causes a negative response of Daily new cases, that are different from China. And it needs 60 working days as reaction time. After 60 working days, the cumulative response remained at -20% means response is numerically equal to 0. The band zone final between -5% and -25%. Compared with China, it has a larger span. Compare the response of two countries. We can get the shocks of the US Shortage news have larger and more persistent effects on it's Daily new cases.

From Figure 16, shock of Chinese Shortage news causes a positive impulse response function of Stringency index, with a large confidence band that intersects the zero line. Here C.I. interval contains the zero line it means that the cumulative response is not statistically different from zero. The US Shortage news causes a positive response of Stringency index. After 70 working days, the cumulative response reaches its maximum, that is 1.4. Steady state of cumulative response means response is numerically equal to 0. The lower band reaches 0.4 and the upper band reaches 1.9.

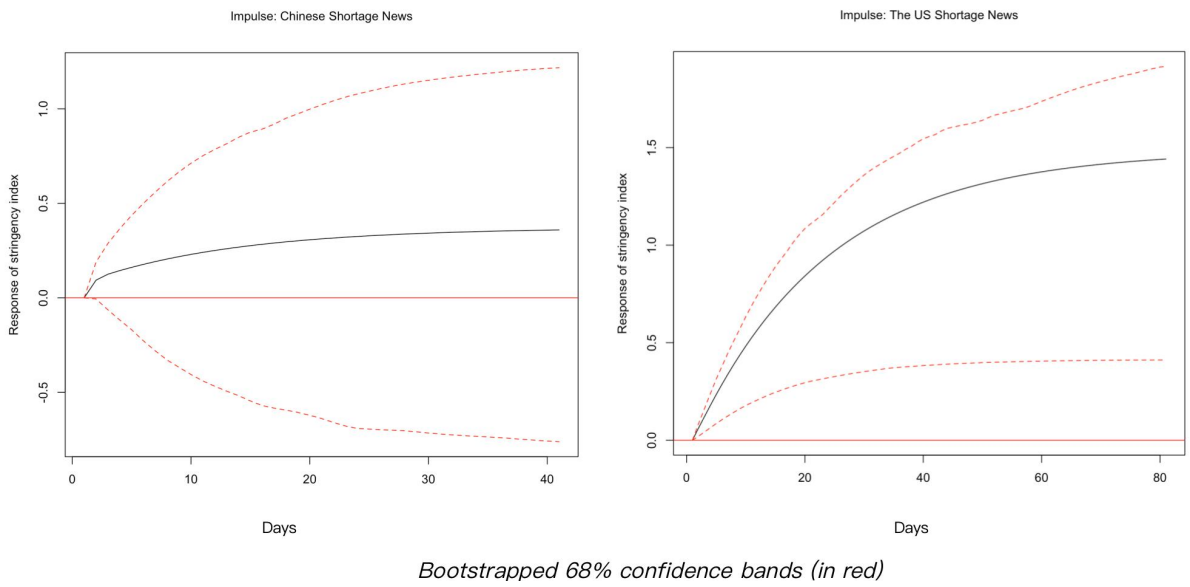

Figure 16. Cumulative responses of Stringency index to Shortage news between China and The US

Compare the response of Stringency index in two countries. It looks like only for the US lockdown measures (proxied through the stringency index) are sensible (in a statistically significant way) to changes in news about mask shortages.

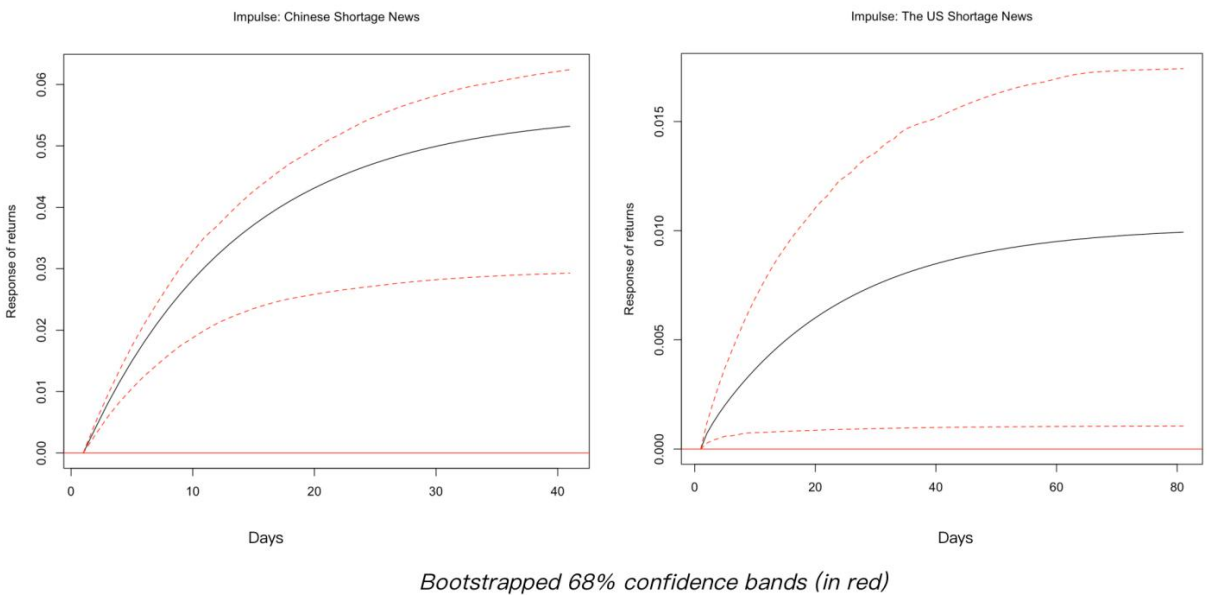

Figure 17. Cumulative responses of Stock returns to Shortage news between China and The US

Figure 17 shows an unitary impulse to Shortage news will cause positive cumulative response of Returns in both countries. After 30 working days, impulse response of Chinese Returns reaches balance state, that is 5%. Which means response is numerically equal to 0. The lower band reaches 3% and the upper band reaches 6.5%. The cumulative response of the US Returns reaches its steady state, close to 1%, 60 working days after the shock. The lower confidence band is relatively close to 0 and the upper band reaches 1.55%.

Compare the response of Returns in two countries. We can know the shocks of the Chinese Shortage news have larger and quicker effects on it's the Returns of mask-related stocks.

3.4 Historical decomposition

We compute the contribution of innovations to 4 endogenous variables (Daily new cases, Stringency index ,Returns and Shortage news) for Chinese orthogonalized VAR(1) model in the period from January 22, 2020 to May 17, 2021 and for the U.S orthogonalized VAR(1) model in the period from January 22, 2020 to May 21, 2021 separately. Historical decomposition could help us to track the influence of the four factors, and hence unveil details about the sign and magnitude of innovations' contribution to changes of other variables across time.

For China

Figure 18. Daily new cases historical decomposition for China

From Figure 18, we can see innovations to Shortage news had a relevant and positive impact on Daily new cases during the first hundred days. The time span was from February to June 2020. news proxy actual shortages, and that hence the lack of masks is actually the reason for the positive impact of shortage news on the number of daily cases in the first 100 observations. The number of people infected with virus increased when they cannot get masks to protect themselves effectively. But after this period the effect became smaller than before as China increased investment in mask manufacturing and encouraged manufacturing industries such as the automobile industry to add more mask production lines to ensure the supply of masks. So this tension had eased, and the influence of the Shortage news had also been reduced. The impact of the Stringency index was always the opposite of that of Daily new cases, just like the mirror effect. We can see that on day 70, 150, 160, 180, 200 and the period between day 250 and 300. Which means the government's strictness of the lockdown policy depends on daily new cases in some way. If there is an abnormal increase of new cases someday, the government will adopt a lockdown policy equivalent to the severity of this situation.

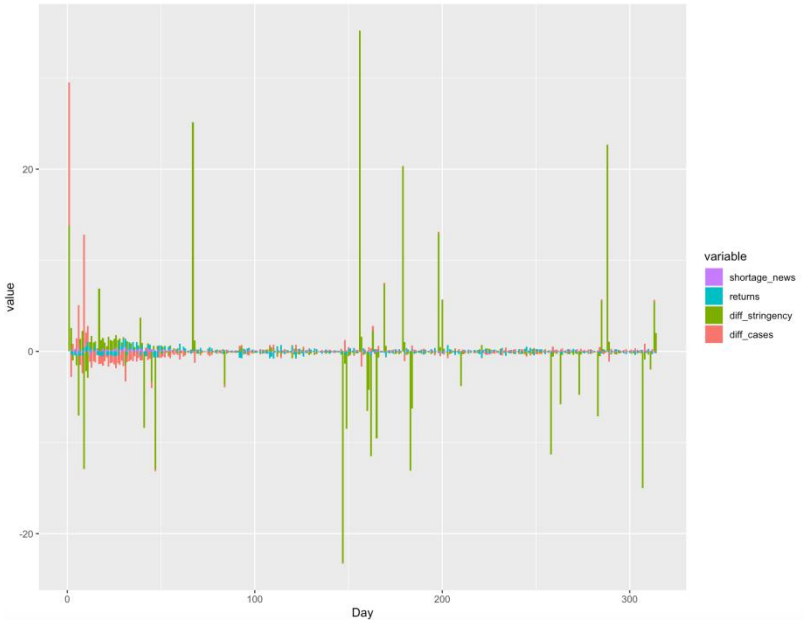

Figure 19. Stringency index historical decomposition for China

From Figure 19, we can see innovations to Daily new cases had the most relevant to the Stringency index. The impact of the Daily new cases was generally the opposite of that of Stringency index. This is consistent with what analyzed above. The effect of Returns and Shortage news were almost null.

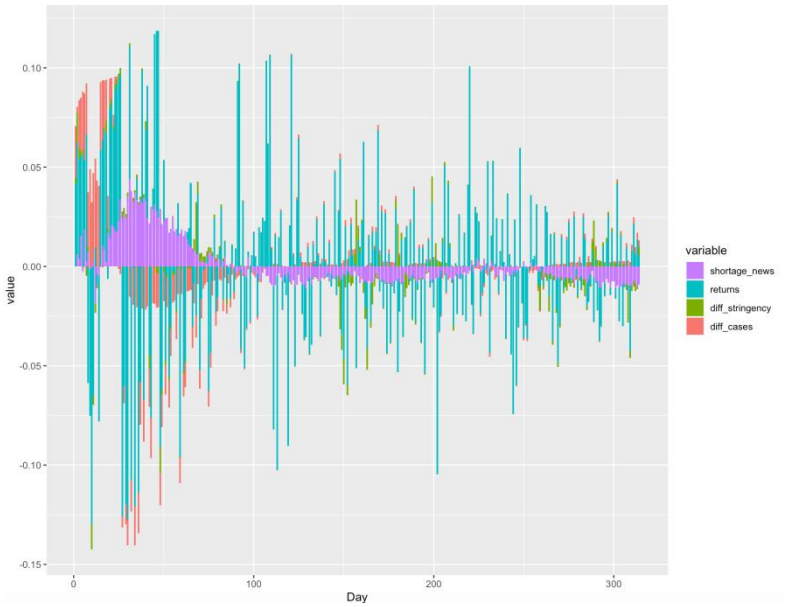

Figure 20. Returns historical decomposition for China

From Figure 20, we can see innovations to Shortage news had a relevant impact on Returns during the

first hundred days. In this period, the effect was positive. This may be because during the first 100 days, the mask shortage news caused people to worry about the supply of raw materials of masks and stimulated the stock price of polyethylene. Later, the shortage of masks had eased, and the impact of news also was reduced. During the first twenty days the effect of Daily new cases had also a positive and significant effect on Returns, but it changed to negative during the period between day 20 and day 100.

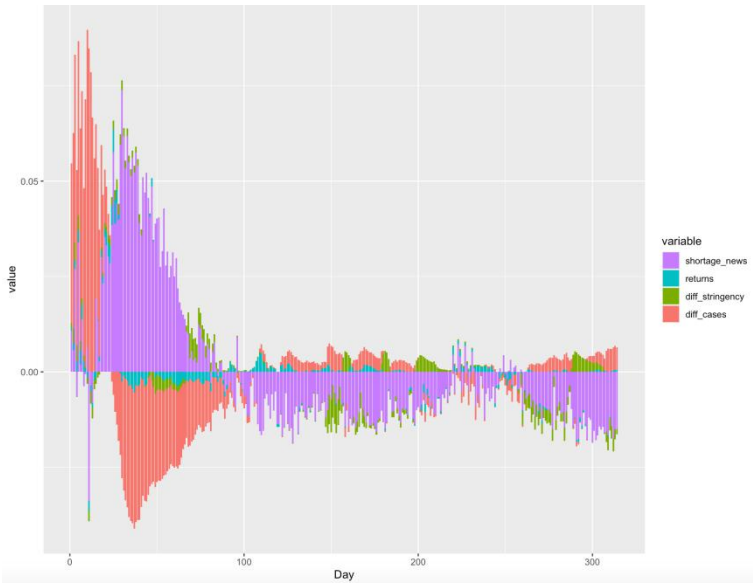

Figure 21. Shortage news historical decomposition for China

From Figure 21, we can see innovations to Daily new cases had the most relevant impact on Shortage news during the first hundred days. In the first twenty days the effect was positive. Because with more people infected, out of anxiety about the future, people will snap up and hoard masks. This aggravated the shortage of masks, correspondingly, the shortage news increased. After twenty days, in early March, in China the pandemic was under control and just few new cases daily. So, the effect of Daily new cases decreased gradually. During the period between day 50 and 70 we also could see the negative effect of Stringency index on Shortage news. The stricter the government's closure policy, the less people go out and less masks would be used. So strict index can alleviate the shortage of masks and reduce the shortage news. The Returns during the first hundred days shows negative effect on Shortage news.

For the U.S.

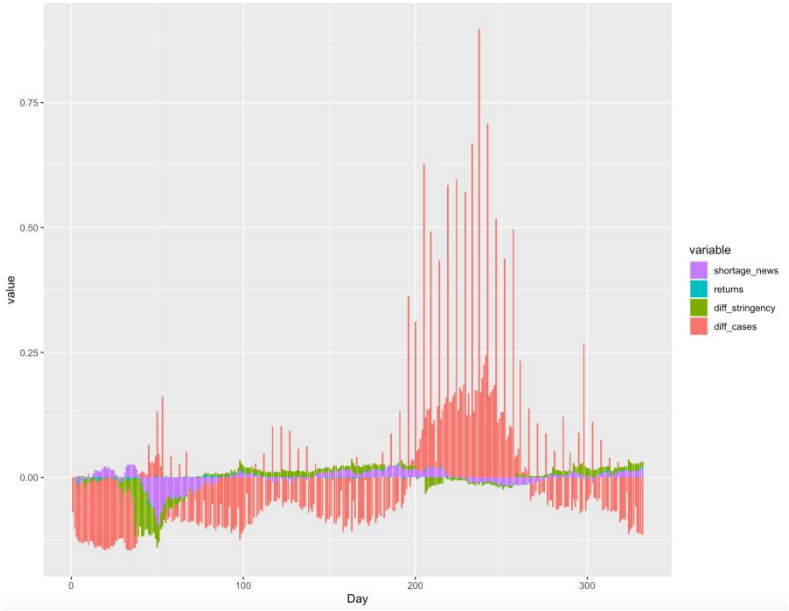

Figure 22. Daily new cases historical decomposition for the U.S

From Figure 22, as we can see besides Daily new cases itself, innovations to Stringency index and Shortage news were more relevant for Daily new cases compared with Returns which showed almost null effect. Shortage news had a positive effect on the Daily new cases during the first forty days. Then it showed a larger magnitude negative effect in the following forty days, which also the peak of the percentage stories about mask shortage. This means during the short period, the Shortage news really had an effect on suppressing Daily new cases. Then in the following days the relevant of Shortage news to Daily new cases turned close to null which was caused by Trump's public speeches on the uselessness of masks. Trump connected masks with politics. A large number of supporters who believe in Trump held parades without wearing masks many times which result the sharpest rise of Daily new cases. And people care less about mask related news. Stringency index had a negligeable effect on Daily new cases during the first 30 days as the U.S only stopped flights with China and the domestic closure policy had not yet started at that time. In the following 40 days, Stringency index showed a negative impact on Daily new cases which means the closure policy was useful in Suppressing the spread of the Covid-19. Then the U.S maintained the high level of closure policy.

From Figure 23, we can see innovations to Daily new cases and Shortage news both had relevance to the Stringency index. The changes of Stringency index were always the opposite of that of the Daily new cases and Shortage news. Which means the the strictness of the closure policy is based on the severity of the pandemic. This also confirms that the formulation of a closed policy can alleviate the shortage of masks and prevent the spread of the virus.

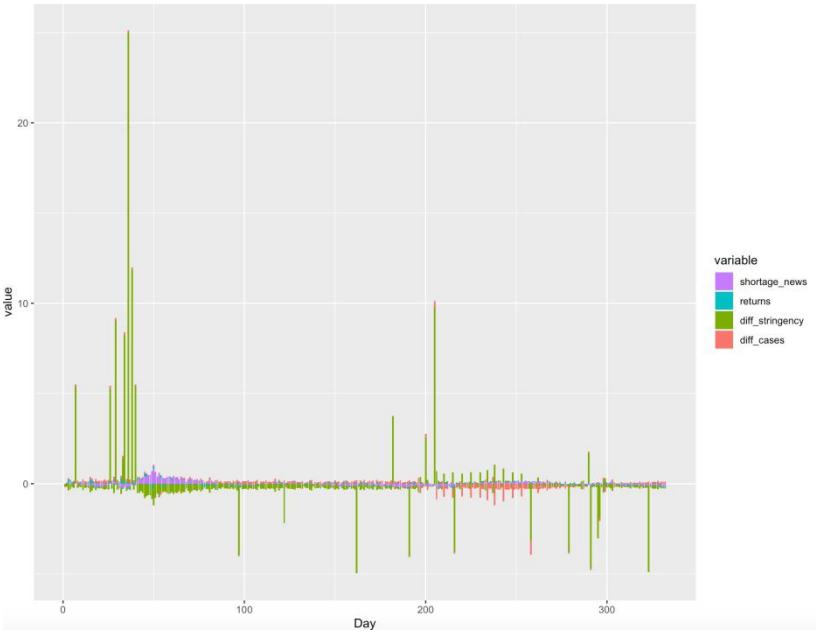

Figure 23. Stringency index historical decomposition for the U.S

From Figure 24, we find that in the first forty days, Stringency index showed a negative impact on Returns. In the following thirty days it turned to positive. Shortage news showed positive effect on polypropylene stock market from day 40 to 80. Unlike Stringency index and Shortage news, Daily new cases showed a very small contribution later, from day 200 to day 250 , it had a relatively positive effect on Returns.

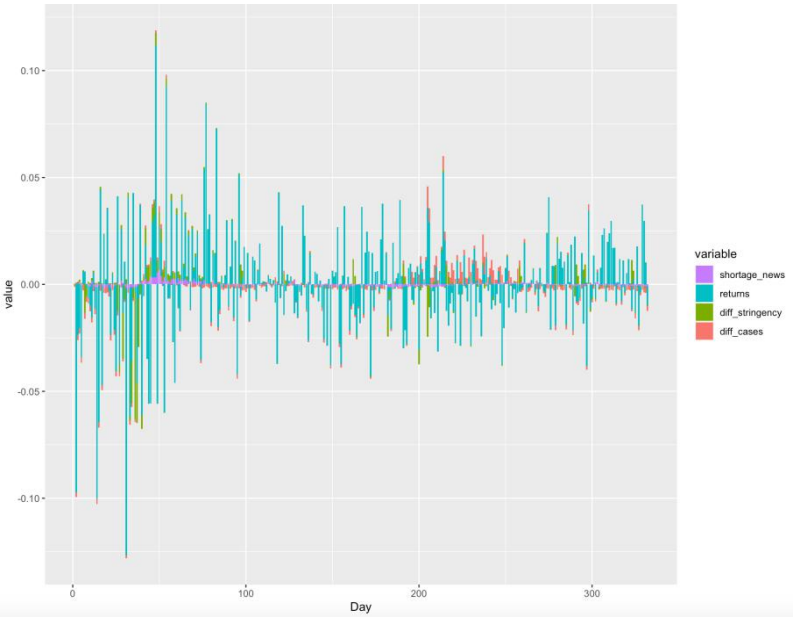

Figure 24. Returns historical decomposition for the U.S.

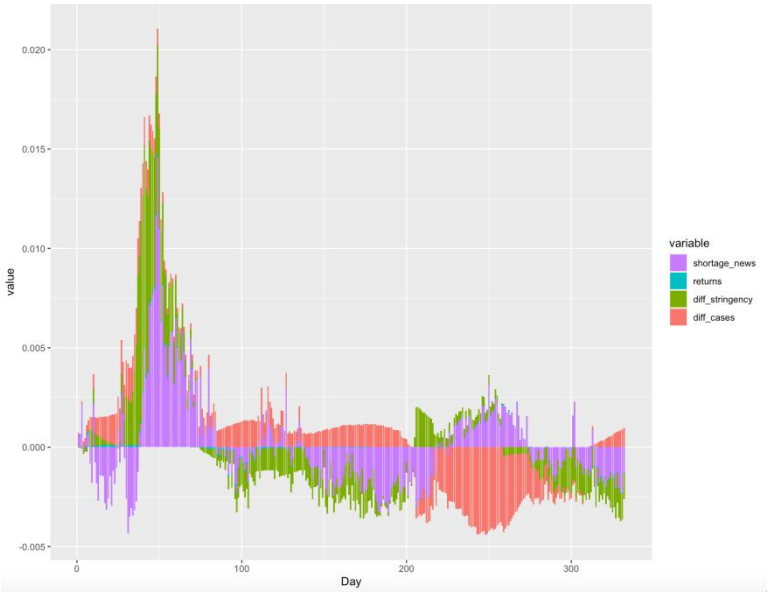

Figure 25. Shortage news historical decomposition for the U.S.

From Figure 25, we can know Returns innovations had almost null contribution to Shortage news. In the first fifty days, the effect of Stringency index and daily new cases are all positive and the influence reached its maximum on the fiftieth day. And during this period, the effect of daily new cases is bigger than Stringency index, as the closure policy at that time was not strict yet. The low-level closure policy didn't alleviate the shortage of masks on the market. During the period from Day 75 to day 200, the effect of Daily new cases kept positive while the Stringency index changed to negative. This means the closure policy began to work to reduce the pressure of mask shortage. And the increasing new cases aggravated the shortage of masks. So, with the increases in the number of infections, there were more news reports about the shortage of masks. Then after day 200, it was winter and the third and most ferocious wave of the pandemic occurred in the United States. The situation hence reversed, the impact of Daily new cases turned to negative and the effect of Stringency index turned to positive again. After the peak of the third wave, from day 250 on, effect of Stringency index on Shortage news turned back negative. So, most of the time, Stringency index held a negative impact on Shortage news, except during the third wave of pandemic.

4. Conclusion

In this paper we used stringency index, daily new cases, mask shortage news and polypropylene stock returns as four endogenous variables in a VAR(1) model of China and the U.S to analyze the relationship between these four factors in two different countries. Research time span of China is from January 22, 2020 to May 17, 2021. Time span of the U.S is from January 22, 2020 to May 21, 2021.

We observed the Historical Decomposition of the time series in two countries, mainly focused on the difference between China and the U.S. After compared our result, we found that at first, in China, Shortage news had a positive and relevant contribution to Daily new cases. Because the number of people infected with virus increased when they cannot get masks to protect themselves effectively. Then as China increased investment in mask manufacturing, this tension had eased. In the U.S, During the first wave of pandemic, Shortage news and Stringency index all showed great negative effect on Daily new cases, which means Shortage news and Stringency index all did work to reduce Daily new cases. But in the most severe third wave, this inhibition was very limited.

For China, mask shortage news and daily new cases both had a positive effect on the Returns in the early days of the outbreak. Which means in China, increase of mask shortage news and daily new cases can arise investors' interest in the raw material stock market such as polypropylene. But for the U.S, the effect on mask shortage news on polypropylene stock returns was so little as to be unnoticeable. Stringency index showed negative impacts on Returns in the beginning, later Daily new cases showed it's positive effect on Returns mainly during the third wave of pandemic. Which means American investors attitude towards polypropylene stock market is different from that of China. In the early period of the pandemic, American investors were more sensitive to the stringency index. While in the worst pandemic period, investors were more likely to be swayed by daily new cases.

Only in China, Returns had an effect on Shortage news. This means in China, the polypropylene stock returns and mask shortage news were closely related and influenced each other. That is very different from American polypropylene stock market.

5. Shortcomings and prospects

The main shortcoming of this paper is in the process lag selection. For the VAR model of the U.S, Schwarz Criterion (SC) showed the best lag was 2, but here in order to simplify and make better comparison with data of China, we choose to estimate a order 1 VAR. This has certainly an influence on the final results. Another limit of this work is number of countries, compare estimates from more countries would make the findings of this research more general.

6. Acknowledgment

First of all, I would like to express my sincere gratitude to my supervisor Carlo Romano Santagiustina. Thank him for always guiding me patiently, and he never scolded me even when I sometimes felt that I was terrible. He respects the topic which I am really interested in and puts forward many suggestions that are beneficial to the development of my thesis from the aspects that I am interested in. The research framework he proposal has kept my mind very clear all the time. Thank him for taking a lot of time to teach me step by step how to use software to build models and how to analyze the results. Eventually, what started as a naive idea in the mind materialized in the real world.

Second, I would like to express my special gratitude to my friends who listened to me patiently and gave me encouragement and support when I was under great pressure. Thanks to all the company that eased my anxiety, which is also a key to my ability to complete this paper.

Last thanks belongs to my family. Thanks for the support of my parents, let me have the experience of leaving China and studying abroad. The outbreak of Covid-19 has separated us for a year and a half. Recently, due to the pressure of thesis and various exams, I have reduced the contact with my family, but they have always understood me, supported me silently, and gave me the courage to persevere.

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